

Distillation of News Flow into Analysis of Stock Reactions

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Abstract

News carry information of market moves. The gargantuan plethora of opinions, facts and tweets on financial business offers the opportunity to test and analyze the

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influence of such text sources on future directions of stocks. It also creates though the necessity to distill via statistical technology the informative elements of this prodigious and indeed colossal data source. Using mixed text sources from professional platforms, blog fora and stock message boards we distill via different lexica sentiment variables. These are employed for an analysis of stock reactions: volatility, volume and returns. An increased (negative) sentiment will influence volatility as well as volume. This influence is contingent on the lexical projection and different across GICS sectors. Based on review articles on 100 S&P 500 constituents for the period of October 20, 2009 to October 13, 2014 we project into BL, MPQA, LM lexica and use the distilled sentiment variables to forecast individual stock indicators in a panel context. Exploiting different lexical projections, and using different stock reaction indicators we aim at answering the following research questions:

- (i) Are the lexica consistent in their analytic ability to produce stock reaction indicators, including volatility, detrended log trading volume and return?
- (ii) To which degree is there an asymmetric response given the sentiment scales (positive v.s. negative)?
- (iii) Are the news of high attention firms diffusing faster and result in more timely and efficient stock reaction?
- (iv) Is there a sector specific reaction from the distilled sentiment measures?

We find there is significant incremental information in the distilled news flow. The three lexica though are not consistent in their analytic ability. Based on confidence bands an asymmetric, attention-specific and sector-specific response of stock reactions is diagnosed.

Keywords: Investor Sentiment, Attention Analysis, Sector Analysis, Volatility Simulation, Trading Volume, Returns, Bootstrap
JEL Classifications: C81, G14, G17

1 Introduction

News are driving financial markets. News are nowadays massively available on a variety of modern digital platforms with a wide spectrum of granularity scales. It is exactly this combination of granularity and massiveness that makes it virtually impossible to process all the news relevant to certain financial assets. How to distinguish between “noise” and “signal” is also here the relevant question. With a few exceptions the majority of empirical studies on news impact work has therefore been concentrated on specific identifiable events like scheduled macroeconomic announcements, political decisions, or asset specific news. Recent studies have looked at continuous news flow from an automated sentiment machine and it has been discovered to be relevant to high frequency return, volatility and trading volume. Both approaches have limitations since they concentrate on identifiable indicators (events) or use specific automated linguistic algorithms.

This paper uses text data of different granularity from blog fora, news platforms and stock message boards. Using several lexical projections, we define pessimistic (optimistic) sentiment with specific meaning as the average proportions of negative (positive) words in articles published on or after trading day t and before trading day $t + 1$, and examine their impacts on stock trading volume, volatility and return. We analyze those effects in a panel data context and study their influence on stock reactions. These reactions might be interesting since large institutions, more sophisticated investors, usually express their views on stock prospective or prediction through published analyst forecasts. However, analysts’ recommendations may be contaminated by their career concerns and compensation scheme; they may also be in alliance with other financial institutions such as investment banks, brokerage houses or target companies (Hong and Kubik, 2003; Liu, 2012). Due to the possible conflicts of interest from analysts and their powerful influence on naive small investors, the opinions from any individuals may be trustworthy since their personal opinions hardly create any manipulation that governs stock reactions. The advent of social media such as *Seeking Alpha* enables small investors to share and express their opinions frequently, real time and responsively.

We show that small investors’ opinions contribute to stock markets and create a ”news-driven” stock reaction. The conversation in the internet or social media is valuable since the

introduction of conversation among a subset of market participants may have large effects on the stock price equilibrium (Cao et al., 2001). Other literature such as Antweiler and Frank (2004), Das and Chen (2007), Chen et al. (2014) demonstrate the value of individual opinions on financial market. They show that small investor opinions predict future stock returns and earnings surprises even after controlling the financial analyst recommendation.

The projections (of a text into sentiment variables) we employ are based on three sentiment lexica: the BL, LM and MPQA lexica. They are used to construct sentiment variables that feed into the stock reaction analysis. Exploiting different lexical projections, and using different stock reaction indicators we aim at answering the following research questions:

- (i) Are the lexica consistent in their analytic ability to produce stock reaction indicators, including volatility, detrended log trading volume and return?
- (ii) To which degree is there an asymmetric response given the sentiment scales (positive v.s. negative)?
- (iii) Are the news of high attention firms diffusing faster and result in more timely and efficient stock reaction?
- (iv) Is there a sector specific reaction from the distilled sentiment measures?

Question (i) addresses the variation of news content across different granularity and lexica. Whereas earlier literature focusses on numerisized input indices like ReutersNewsContent or Google SVI, we would like to investigate the usefulness of automated news inputs for e.g. statistical arbitrage algorithms. Question (ii) examines the effect of different sentiment scales on stock reactions like volatility, trading volume and returns. Three lexica are employed that are producing different numerical intervals and thus raise the concern of how much structure is captured in the resulting sentiment measure. An answer to this question will give us insight into whether the well known asymmetric response (bad vs. good news) is appropriately reflected in the lexical projections. Question (iii) and (iv) finally analyze whether stylized facts play a role in our study. This is answered via a panel data scheme using GICS sector indicators and attention ratios.

Groß-Klußmann and Hautsch (2011) analyse in a high frequency context market reactions to the intraday stock specific “Reuters NewsScope Sentiment” engine. Their findings

support the hypothesis of news influence on volatility and trading volume, but are in contrast to our study based on a single news source and confined to a limited number of assets for which high frequency data are available.

Antweiler and Frank (2004) analyze text contributions from stock message boards and find that the amount and bullishness of messages have predictive value for trading volume and volatility. On message boards, the self-disclosed sentiment to hold a stock position is not bias free, as indicated in Zhang and Swanson (2010). Tetlock (2007) concludes that negative sentiment in a Wall Street Journal column has explanatory power for downward movement of the Dow Jones. Bollen et al. (2011) classify messages from the micro-blogging platform Twitter in six different mood states and find that public mood helps to predict changes in daily Dow Jones values. Zhang et al. (2012) extends this by filtering the Twitter messages (tweets) for keywords indicating a financial context and they consider different markets such as commodities and currencies. Si et al. (2013) use a refined filtering process to obtain stock specific tweets and conclude that topic based Twitter sentiment improves day-to-day stock forecast accuracy. Sprenger et al. (2014) also use tweets on stock level and conduct that the number of retweets and followers may be used to assess the quality of investment advice. Chen et al. (2014) use articles and corresponding comments on *Seeking Alpha*, a social media platform for investment research, and show predictive value of negative sentiment for stock returns and earnings surprises. According to Wang et al. (2014), the correlation of Seeking Alpha sentiment and returns is higher than between returns and sentiment in Stocktwits, messages from a micro-blogging platform specialized in finance.

Using either individual lexical projections or a sentiment index comprising the common component of the three lexical projections, we find that the text sentiment shows an incremental influence on the stocks collected from S&P 500 constituents. An asymmetric response of the stock reaction indicators to the negative and positive sentiments is confirmed and supports the leverage effect, that is, the stocks react to negative sentiment more. The reaction to the distilled sentiment measures is attention-specific and sector-specific as well. Due to the advent of social media, the opinions of small traders that have been ignored from past till now, do shed some light on stock market activity. The rest

of the paper is organized as follows. Section 2 describes the data gathering process and summarizes both definitions of variables and introduces the different sentiment lexica. In Section 3, we present the regression and simulation results using the entire sample and samples grouped by attention ratio and sectors. The conclusion follows in Section 4.

2 Data

2.1 Text Sources and Stock Data

While there are many possible sources of financial articles on the web, there are also legal and practical obstacles to clear before obtaining the data. The text source *Seeking Alpha*, as used in Chen et al. (2014), prohibits any application of automatic programs to download parts of the website (web scraper) in their Terms of Use (TOS). While the usage of web scrapers for non-commercial academic research is principally legal, these TOS are still binding as stated in Truyens and Eecke (2014). For messages on Yahoo! Finance, another popular source of financial text data used in Antweiler and Frank (2004); Zhang and Swanson (2010), the TOS are not a hindrance but the limited message history that is provided. As of December 2014, only the last 10,000 messages are shown in each stock specific message board and this roughly corresponds to a two-month-period for stocks that people talk frequently about like Apple. In opposition to these two examples, NASDAQ offers a platform for financial articles by selected contributors including social media websites such as *Seeking Alpha* and *Motley Fool*, investment research firms such as Zacks. Neither do the TOS prohibit web scraping nor is the history of shown articles limited. We have collected 116,691 articles and corresponding stock symbols, spanning roughly five years from October 20, 2009 to October 13, 2014. The data is downloaded by using a self-written web scraper to automate the downloading process.

The process of gathering and processing the article data and producing the sentiment scores can be seen in Figure 1. Firstly, the URLs of all articles on NASDAQ are gathered and every webpage containing an article is downloaded. Each URL can be used in the next steps as unique identifier of individual articles to ensure that one article is not used twice due to real-time updates of the NASDAQ webpage. In the pre-processing step,

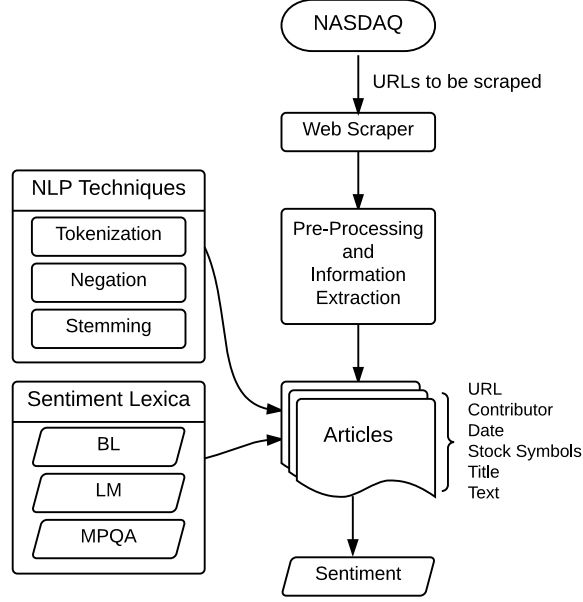


Figure 1: Flowchart of data gathering process

the page navigation and design elements of NASDAQ are removed. The specifics of each article, namely contributor, publication date, mentioned stock symbols, title and article text, are identified and read out. In case of the article text, the results are stored in individual text files. This database is available for research purposes at [RDC](#), CRC 649, Humboldt-Universität zu Berlin.

Furthermore, we collected stock specific financial data. Daily prices and trading volume, defined as number of shares traded, of all stock symbols that are S&P 500 constituents are collected from Datastream while Compustat is used to gather Global Industry Classification Standard (GICS) sector, total debt and assets for these stocks.

We consider three stock reaction indicators: volatility, detrended log trading volume and return. For stock symbol i and trading day t , we compute the Garman and Klass (1980) range-based measure of volatility defined as:

$$\sigma_{i,t} = 0.511(u - d)^2 - 0.019 \{c(u + d) - 2ud\} - 0.838c^2 \quad (1)$$

$$\text{with } u = \log(P_{i,t}^H) - \log(P_{i,t}^L),$$

$$d = \log(P_{i,t}^L) - \log(P_{i,t}^O),$$

$$c = \log(P_{i,t}^C) - \log(P_{i,t}^O),$$

where $P_{i,t}^H$, $P_{i,t}^L$, $P_{i,t}^O$, $P_{i,t}^C$ are the daily highest, lowest, opening and closing stock prices, respectively. Chen et al. (2006) and Shu and Zhang (2006) show that the Garman and Klass range-based measure of volatility essentially provides equivalent results to high-frequency realized volatility. In addition, it avoids the problems caused by microstructure effects. Following Girard and Biswas (2007), we estimate the detrended log trading volume for each stock by using a quadratic time trend equation:

$$V_{i,t}^* = \alpha + \beta_1 t + \beta_2 t^2 + V_{i,t}, \quad (2)$$

where $V_{i,t}^*$ corresponds to the raw daily log trading volume, and the detrended log trading volume $V_{i,t}$ are the residuals. We avoid imposing a look-ahead bias by using a rolling window of 120 observations and estimating a one-step ahead pseudo out-of-sample forecast. Furthermore, we calculate the log returns as $R_{i,t}$.

We focus on 100 stock symbols that are S&P 500 constituents on all 1,255 trading days between October 20, 2009 and October 14, 2014, that belong to one of nine major GICS sectors for stock symbols that are S&P 500 constituents on at least one trading day during this period, and that have the most trading days with articles. The distribution of GICS sectors among these 100 symbols are given in Table 1. Out of the 116,691 articles collected, there are 43,459 articles associated with these 100 stock symbols; the number of articles for these stocks range from 340 to 5435, and the number of trading days with articles ranges from 271 to 1039. Most of the articles are not about one single symbol but contain references to several stocks.

2.2 Sentiment Lexica and Sentiment Variables

To distill sentiment variables from each article, we use and compare three sentiment lexica. The first lexicon (BL) is a list of 6,789 sentiment words (2,006 positive and 4,783 negative) compiled over many years starting from Hu and Liu (2004) and maintained by [Bing Liu at University of Chicago, Illinois](#). We filter each article with this lexicon and calculate the proportions of positive and negative words. The second lexicon (LM) is based on Loughran and McDonald (2011) which is specifically designed for financial applications, and contains 354 positive words, 2,329 negative words, 297 uncertainty words, 886 litigious words, 19

GICS Sector	No. Stocks
Consumer Discretionary	21
Consumer Staples	9
Energy	6
Financials	12
Health Care	15
Industrials	10
Information Technology	21
Materials	4
Telecommunication Services	2

Table 1: Distribution of GICS sectors among the 100 stock symbols

strong modal words and 26 weak modal words. To be consistent with the usage of the other lexica, we only consider the list of positive and negative words and calculate the proportions of positive and negative words for each article.

The third lexicon is the MPQA (Multi-Perspective Question Answering) Subjectivity Lexicon by Wilson et al. (2005) which we later refer to as the MPQA lexicon. This lexicon contains 8,222 entries. In order to show the rather tedious distillation process let us look at six example entries:

```

type=weaksubj len=1 word1=abandoned pos1=adj stemmed1=n priorpolarity=negative
type=weaksubj len=1 word1=abandonment pos1=noun stemmed1=n priorpolarity=negative
type=weaksubj len=1 word1=abandon pos1=verb stemmed1=y priorpolarity=negative
type=strongsubj len=1 word1=abase pos1=verb stemmed1=y priorpolarity=negative
type=strongsubj len=1 word1=abasement pos1=anypos stemmed1=y priorpolarity=negative
type=strongsubj len=1 word1=abash pos1=verb stemmed1=y priorpolarity=negative

```

Here **type** refers to whether the word is classified as strongly subjective, indicating that the word is subjective in most contexts, or weakly subjective, indicating that the word only has certain subjective usages; **len** denotes the length of the word; **word1** is the spelling of the word; **pos1** is part-of-speech tag of the word, which could take values adj (adjective), noun, verb, adverb, or anypos (any part-of-speech tag); **stemmed1** is an indicator for whether this word is stemmed, where stemming refers to the process of reducing inflected (or sometimes

derived) words to their word stem, base or root form; and **priorpolarity** refers to polarity of the word, which could take values negative, positive, neutral, or both (both negative and positive). To be consistent with the usage of the other two lexica, we only consider positive and negative polarity.

We first use the NLTK package in Python to tokenize sentences and (un-stemmed) words in each article, and derive the part-of-speech tagging for each word. We filter each tokenized article with the list of entries with **stemmed1=n** in the MPQA lexicon to count the number of positive and negative word. We then use the Porter Stemmer in the NLTK package to stem each word and filter each article with the list of entries with **stemmed1=y** in the MPQA lexicon. If a word has been assigned polarity in the first filtering step, it will no longer be counted in the second filtering step. For each article, we can thus count the numbers of negative and positive words, and divide them by the length of the article to get the proportions of negative and positive words.

Regardless of which lexicon is used, we use a variation of the approach in Hu and Liu (2004) to account for sentiment negation. If the word distance between a negation word (“not”, “never”, “no”, “neither”, “nor”, “none”, “n’t”) and the sentiment word is no larger than 5, the positive or negative polarity of the word is changed to be the opposite of its original polarity.

Among the words that appear at least three times in our list of articles, there are 470 positive and 918 negative words that are unique to the BL lexicon, 267 positive and 916 negative words that are unique to the LM lexicon, and 512 positive and 181 negative words that are unique to the MPQA lexicon. The LM lexicon contains less unique positive words than the other two lexica, and the MPQA lexicon contains many unique negative words than the other two lexica. Table 2 presents the lists of ten most frequent positive words and ten most frequent negative words that are unique to these three lexica. Since the BL and MPQA lexica are designed for general purpose and the LM lexicon is designed specifically for financial applications, the unique words under the BL and MPQA lexica indeed look more general.

Words in the general-purpose lexica may also be misclassified for financial applications; for example, the word “proprietary” in the negative list of the BL lexicon may refer to

things like “a secure proprietary operating system that no other competitor can breach” and hence have a positive tone in financial applications, and the word “division” in the negative list of the MPQA lexicon may only refer to divisions of companies. However, financial analysis using textual information is unavoidably noisy, and words in the LM lexicon can also be misclassified; for example, the word “closing” in the negative list of the LM lexicon may actually refer to a positive event of closing a profitable deal. Also, the LM lexicon does not take into account financial words such as “debt” and “risks” in the BL lexicon.

BL		LM		MPQA	
Positive (470)	Negative (918)	Positive (267)	Negative (916)	Positive (512)	Negative (181)
Available	Debt	Opportunities	Declined	Just	Low
(5,836)	(12,540)	(4,720)	(9,809)	(17,769)	(12,739)
Led	Fell	Strength	Dropped	Help	Division
(5,774)	(9,274)	(4,393)	(4,894)	(17,334)	(5,594)
Lead	Fool	Profitability	Late	Profit	Least
(4,711)	(5,473)	(4,174)	(4,565)	(15,253)	(5,568)
Recovery	Issues	Highest	Claims	Even	Stake
(4,357)	(3,945)	(3,409)	(3,785)	(13,780)	(4,445)
Work	Risks	Greater	Closing	Deal	Slightly
(3,808)	(2,850)	(3,321)	(3,604)	(13,032)	(3,628)
Helped	Issue	Surpassed	Closed	Interest	Close
(3,631)	(2,821)	(2,464)	(3,378)	(12,237)	(3,105)
Enough	Falling	Enable	Challenges	Above	Trial
(3,380)	(2,768)	(2,199)	(2,574)	(12,203)	(2,544)
Pros	Aggressive	Strength	Force	Accord	Decrease
(2,841)	(1,796)	(2,157)	(2,157)	(11,760)	(2,205)
Integrated	Hedge	Alliance	Unemployment	Natural	Disease
(2,652)	(1,640)	(1,842)	(2,062)	(10,135)	(2,001)
Savings	Proprietary	Boosted	Question	Potential	Little
(2,517)	(1,560)	(1,831)	(1,891)	(9,905)	(1,775)

Table 2: Lists of ten most frequent positive words and ten most frequent negative words that are unique to the BL, MPQA or LM lexica, along with their frequencies given in parentheses.

We next investigate the pairwise relationship among the above three lexica. Among

the words that appear at least three times in our list of articles, there are 131 positive and 322 negative words that are shared only by the BL and LM lexica, 971 positive and 1164 negative words that are shared only by the BL and MPQA lexica, and 32 positive and 30 negative words that are shared only by the LM and MPQA lexica. It is not surprising that the two general-purpose lexica, BL and MPQA, share the most positive and negative words. Out of the two general-purpose lexica, BL lexicon shares more positive and negative words with the special-purpose LM lexicon. Table 3 presents the lists of ten most frequent positive words and ten most frequent negative words that are shared only by two of these three lexica. Words shared by the two general-purpose lexica (BL and MPQA) may be misclassified for financial applications; for example, the word “gross” shared by the negative lists of these two lexica may refer to “the annual gross domestic product” and have a neutral tone. However, words shared by the LM lexicon and one of the general-purpose lexica may also be classified; for example, the word “critical” shared by the negative lists of the BL and LM lexica may appear in sentences such as “mobile devices are becoming critical tools in the worlds of advertising and market research” and have a positive tone.

The above discussion shows that projections using the three lexica are all noisy, therefore it is worthwhile to compare results from these projections. For each stock symbol i and each trading day t , we derive the sentiment variables listed in Table 4 based on articles associated with symbol i and published on or after trading day $t - 1$ and before trading day t .

3 Empirical Results

3.1 Entire Sample Results

3.1.1 Descriptive Statistics and Comparison of the Lexical Projections

Table 5 presents summary statistics of the sentiment variables derived using the BL, LM and MPQA lexical projections for 43,569 symbol-day combinations with $I_{i,t} = 1$. This number is slightly different from the number of articles associated with the 100 selected symbols (43,459), since an article can be associated with multiple symbols. The positive proportion is the largest under the MPQA projection, and the smallest under the LM projection. The

BL and LM		BL and MPQA		LM and MPQA	
Positive (131)	Negative (322)	Positive (971)	Negative (1164)	Positive (32)	Negative (30)
Gains	Losses	Free	Gross	Despite	Against
(7,604)	(5,938)	(133,395)	(8,228)	(7,413)	(8,877)
Gained	Missed	Well	Risk	Able	Cut
(7,493)	(3,165)	(3,0270)	(7,471)	(5,246)	(3,401)
Improved	Declining	Like	Limited	Opportunity	Challenge
(7,407)	(3,053)	(24,617)	(5,884)	(4,398)	(1,042)
Improve	Failed	Top	Motley	Profitable	Serious
(5,726)	(2,421)	(14,899)	(5,165)	(3,580)	(1,022)
Restructuring	Concerned	Guidance	Crude	Efficiency	Contrary
(3,210)	(1,991)	(11,715)	(5,109)	(2,615)	(401)
Gaining	Declines	Significant	Cloud	Popularity	Severely
(3,150)	(1,654)	(10,576)	(4,906)	(1,588)	(348)
Enhance	Suffered	Worth	Fall	Exclusive	Despite
(2,753)	(1,435)	(10,503)	(4,732)	(1,225)	(342)
Outperform	Weaker	Gold	Mar	Tremendous	Argument
(2,518)	(1,288)	(9,303)	(3,190)	(611)	(324)
Stronger	Critical	Support	Hard	Dream	Seriously
(1,657)	(1,131)	(9,120)	(2,957)	(581)	(240)
Win	Drag	Recommendation	Cancer	Satisfaction	Staggering
(1,491)	(1,095)	(8,993)	(2,521)	(410)	(209)

Table 3: Lists of ten most frequent positive words and ten most frequent negative words that are shared only by BL and LM lexica, only by BL and MPQA lexica, or only by LM and MPQA lexica, along with their frequencies given in parentheses.

negative proportions under the three projections are similar. Polarity in Table 5 measures the relative dominance between positive sentiment and negative sentiment. For example, the situation, $Pos_{i,t}(\text{BL}) > Neg_{i,t}(\text{BL})$, accounts for 88.04% of the 43,569 observations. Note that under each projection, there are a small percentage of the observations for which $Pos_{i,t} = Neg_{i,t}$. Under both the BL and MPQA projections, positive sentiment is more dominant and widespread than negative sentiment. The LM projection, however, results in a relative balance between positive and negative sentiment.

Sentiment Variable	Description
$I_{i,t}$	Indicator for whether there is an article.
$Pos_{i,t}$ (BL)	The average proportion of positive words using the BL lexicon.
$Neg_{i,t}$ (BL)	The average proportion of negative words using the BL lexicon.
$Pos_{i,t}$ (LM)	The average proportion of positive words using the LM lexicon.
$Neg_{i,t}$ (LM)	The average proportion of negative words using the LM lexicon.
$Pos_{i,t}$ (MPQA)	The average proportion of positive words using the MPQA lexicon.
$Neg_{i,t}$ (MPQA)	The average proportion of negative words using the MPQA lexicon.

Table 4: Sentiment variables for articles published on or after trading day $t - 1$ and before trading day t .

Variable	$\hat{\mu}$	$\hat{\sigma}$	Max	Q1	Q2	Q3	Polarity
$Pos_{i,t}$ (BL)	0.033	0.012	0.134	0.025	0.032	0.040	88.04%
$Neg_{i,t}$ (BL)	0.015	0.010	0.091	0.008	0.014	0.020	10.51%
$Pos_{i,t}$ (LM)	0.014	0.007	0.074	0.009	0.013	0.018	55.70%
$Neg_{i,t}$ (LM)	0.012	0.009	0.085	0.006	0.011	0.016	40.17%
$Pos_{i,t}$ (MPQA)	0.038	0.012	0.134	0.031	0.038	0.045	96.26%
$Neg_{i,t}$ (MPQA)	0.013	0.008	0.133	0.007	0.012	0.017	2.87%

Sample mean, sample standard deviation, maximum value, 1st, 2nd and 3rd quartiles, and polarity.

Table 5: Summary Statistics for Text Sentiment Variables

To check whether the sentiment polarity actually reflects the sentiment of the articles, we actually carefully checked and read the contents of 100 randomly selected articles and manually classified their polarity (positive, negative and neutral), and also use the lexical projections to automatically classify these articles as follows. If the proportion of positive words for an article is larger than (or small than, or equal to) the proportion of negative words for the same article, then this article is automatically classified as positive (or negative, or neutral). Table 6 reports the results. It appears that the BL and MPQA projections

Manual Label	BL Label			LM Label			MPQA Label			Total
	Pos	Neg	Neu	Pos	Neg	Neu	Pos	Neg	Neu	
Pos	56	4	1	41	12	8	61	0	0	61
Neg	9	2	1	0	9	3	9	2	1	12
Neu	22	5	0	10	15	2	26	0	1	27
Total	87	11	2	51	36	13	96	2	2	100

Table 6: Sentiment Classification Results for 100 Randomly Selected Articles

put too much weight on positive sentiment, and are not powerful in detecting negative sentiment. In contrast, the LM sentiment is powerful in detecting negative sentiment, but is not so good in detecting positive sentiment.

Figure 2 and 3 respectively show the monthly correlation between positive and negative proportions under two of the three projections. In general, the negative proportions are more correlated than positive proportions. Also, the correlation between the BL and LM projections and that between the BL and MPQA projections are larger than the correlation between the LM and MPQA projections, which is consistent with the discussion about the list of words shared by two of the three projections (see Table 3).

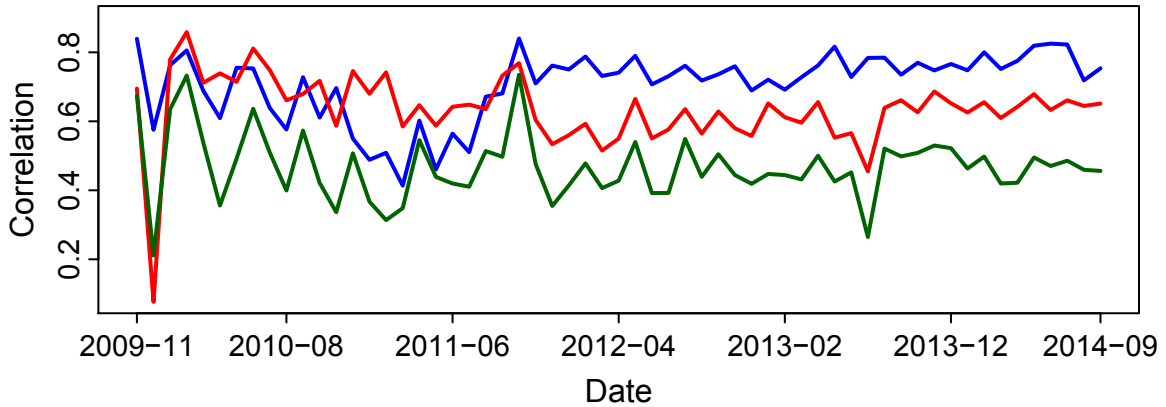


Figure 2: Monthly correlation between positive sentiment: BL and LM, BL and MPQA, LM and MPQA

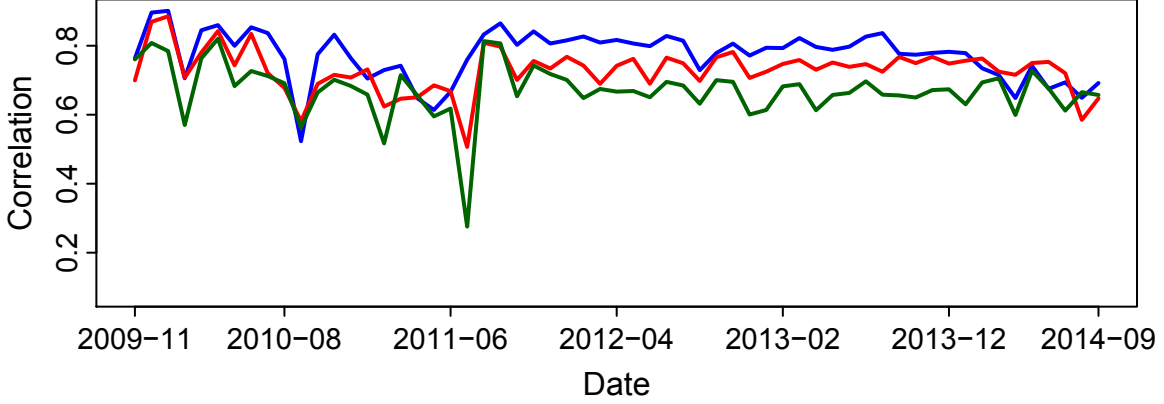


Figure 3: Monthly correlation between negative sentiment: BL and LM, BL and MPQA, LM and MPQA

3.1.2 Main Results

Recall from Section 2.1 that we focus on three stock reaction indicators: range-based measure of volatility $\sigma_{i,t}$ as in (1), detrended log trading volume $V_{i,t}$ as in (2) and log returns $R_{i,t}$. We consider analyzing these three indicators with one trading day into the future, and use the following (separate) panel regressions.

$$\sigma_{i,t+1} = \alpha_i + \beta_1 I_{i,t} + \beta_2 Pos_{i,t} + \beta_3 Neg_{i,t} + \beta_4^\top X_{i,t} + \gamma_i + \varepsilon_{i,t}, \quad (3)$$

$$V_{i,t+1} = \alpha_i + \beta_1 I_{i,t} + \beta_2 Pos_{i,t} + \beta_3 Neg_{i,t} + \beta_4^\top X_{i,t} + \gamma_i + \varepsilon_{i,t}, \quad (4)$$

$$R_{i,t+1} = \alpha_i + \beta_1 I_{i,t} + \beta_2 Pos_{i,t} + \beta_3 Neg_{i,t} + \beta_4^\top X_{i,t} + \gamma_i + \varepsilon_{i,t}. \quad (5)$$

where γ_i is the fixed effect for stock symbol i satisfying $\sum_i \gamma_i = 0$. $X_{i,t}$ is a vector of control variables that includes a set of market variables to control for systematic risk such as (1) S&P 500 index return ($R_{M,t}$) to control for general market returns; (2) the CBOE VIX index on date t to measure the generalized risk aversion (VIX_t); and a set of firm idiosyncratic variables such as (3) the lagged volatility ($\sigma_{i,t}$); (4) the lagged return ($R_{i,t}$); (5) the lagged detrended trading volume ($V_{i,t}$), where the lagged dependent variable is used to capture the persistence and omitted variables. These three indicators essentially have a triple dynamic correlation, and they have been modeled as a trivariate vector autoregressive (VAR) model, see Chen et al. (2001) and Chen et al. (2002). Our indicators in Eqs.(4) to

(5) not only have themselves dynamic relationship with their lagged values, but also are impacted from the other lagged indicators.

To answer our research question (i), if the three lexica are not consistent in their analytic ability to produce stock reaction indicators, we would expect that the value of β_1 , β_2 or β_3 is different across three lexical projections. For question (ii), if the positive and negative sentiments have asymmetric impacts, we would expect that β_2 and β_3 have different signs or significance. To address question (iii), we would expect that the value of β_1 , β_2 or β_3 varies with different attention levels and in particular that the coefficient size is larger for higher attention firms. As to question (iv), we would expect that the value of β_1 , β_2 or β_3 is sector-specific.

We will discuss analysis of different attention levels and different sectors respectively in Sections 3.2 and 3.3, and focus now on the entire sample. The regression results are given in Table 7. Results in Panel A indicate that the negative sentiment distilled using the BL and LM methods is significantly positively related to future volatility, but the arrival of articles ($I_{i,t}$) and the positive sentiment do not carry information for future volatility. Results in Panel B show that the positive and negative sentiment have asymmetric strong impacts on future detrended trading volume: the negative sentiment across three lexica strongly drives up future detrended trading volume, whereas the positive sentiment distilled using the BL and MPQA methods is strongly negatively related to future detrended trading volume. The arrival of articles also strongly drives up future detrended trading volume across three lexica. As to future returns in Panel C, across three lexica, the positive sentiments are strongly positively related to future returns whereas the negative sentiment is unrelated to future returns; only under the BL projection, the arrival of articles is negatively related to future returns.

From Table 7, we know that at least one for sentiment variables ($I_{i,t}$, $Pos_{i,t}$, $Neg_{i,t}$) is significant in the entire panel analysis, and the LM lexicon seems more profound than the other two measures. It is difficult to diagnose a consensusual performance because each lexicon may not fully reflect the complete sentiment and may have its own idiosyncratic nature as being evident from Table 2. To overcome this problem that none of the lexica is perfectly complete, we design an artificial sentiment index: the first principal component,

Variable	BL		LM		MPQA		PCA	
	Panel A: Future Volatility $\sigma_{i,t+1}$							
$I_{i,t}$	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
$Pos_{i,t}$	-0.002	(0.002)	-0.001	(0.003)	-0.001	(0.002)	-0.001	(0.002)
$Neg_{i,t}$	0.005*	(0.003)	0.006**	(0.003)	0.004	(0.003)	0.004**	(0.002)
$R_{M,t}$	0.001	(0.002)	0.002	(0.002)	0.002	(0.002)	0.001	(0.002)
VIX_t	0.004***	(0.001)	0.003***	(0.001)	0.003***	(0.001)	0.004***	(0.001)
$\sigma_{i,t}$	0.026***	(0.003)	0.023***	(0.003)	0.023***	(0.003)	0.026***	(0.003)
$R_{i,t}$	-0.006***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)
$V_{i,t}$	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
	Panel B: Future Detrended Log Trading Volume $V_{i,t+1}$							
$I_{i,t}$	0.047***	(0.007)	0.032***	(0.005)	0.050***	(0.007)	0.049***	(0.008)
$Pos_{i,t}$	-0.671***	(0.158)	-0.233	(0.259)	-0.618***	(0.157)	-0.470***	(0.116)
$Neg_{i,t}$	0.888***	(0.197)	0.768***	(0.207)	0.907***	(0.239)	0.589***	(0.136)
$R_{M,t}$	-1.733***	(0.142)	-1.730***	(0.142)	-1.727***	(0.142)	-1.731***	(0.142)
VIX_t	1.174***	(0.062)	1.176***	(0.062)	1.175***	(0.062)	1.174***	(0.062)
$\sigma_{i,t}$	3.031***	(0.213)	3.038***	(0.213)	3.036***	(0.213)	3.032***	(0.213)
$R_{i,t}$	0.181**	(0.072)	0.181**	(0.072)	0.179**	(0.072)	0.181**	(0.072)
	Panel C: Future Returns $R_{i,t+1}$							
$I_{i,t}$	-0.001**	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.001**	(0.000)
$Pos_{i,t}$	0.021***	(0.007)	0.016***	(0.005)	0.016**	(0.007)	0.015***	(0.005)
$Neg_{i,t}$	-0.000	(0.008)	-0.006	(0.009)	-0.006	(0.011)	-0.003	(0.006)
$R_{M,t}$	0.025***	(0.007)	0.025***	(0.007)	0.025***	(0.007)	0.025***	(0.007)
VIX_t	0.167***	(0.003)	0.167***	(0.003)	0.167***	(0.003)	0.167***	(0.003)
$\sigma_{i,t}$	-0.047***	(0.010)	-0.047***	(0.010)	-0.047***	(0.010)	-0.047***	(0.010)
$R_{i,t}$	-0.011***	(0.003)	-0.011***	(0.003)	-0.011***	(0.003)	-0.011***	(0.003)

*** refers to a p value less than 0.01, ** refers to a p value more than or equal to 0.01 and smaller than 0.05, and

* refers to a p value more than or equal to 0.05 and less than 0.1. Values in parentheses are standard errors.

Table 7: Entire Panel Regression Results

to capture a common component of three lexica and to consider the fact from Figures 2 and 3 that they reveal the shared sentiment. The positive (negative) sentiment index explains 96.71% (92.58%) of the total sample variance. As seen in the last column of Table 7, these general positive and negative sentiment indices are beneficial to achieve more consistent and interpretable results. The negative sentiment index spurs the future stock volatility and trading volume. However, the positive sentiment index has very restrictive influence on future volatility, and suppresses the trading volume but increases stock returns.

3.1.3 Monte Carlo Simulation based on Entire Sample Results

The text sentiment effects, as reported in Table 7, allow us deeper insights and analysis. More precisely we may address the important question of asymmetric reactions on the given sentiment scales. In order to do so we employ Monte Carlo techniques to investigate different facets of the sentiment effects. These are (1) to simulate the appearance of articles with presumed probabilities; (2) to provide a realistic set of scenarios regarding the frequency and content (positive v.s. negative) of articles; (3) to obtain an exponential volatility induced by the generated article (using Table 7); (4) to demonstrate the impact of synthetic text on future volatility; (5) to visualize and test an asymmetry effect as formulated in research question 2.

The simulation scenarios (for each variable involved) are summarized briefly as follows. We employ a Bernoulli random variable $I_{i,t}$ indicating that an article arrives at a specific frequency p_i , as this is a relevant fact each individual symbol (firm). Given the outcome of this article indicator, one generates the corresponding positive and negative proportions through a uniform distribution on $(0, \max_i)$ where the upper bounds \max_i for both positive and negative proportions are fixed at their historically highest points for each symbol. To take into account the inherent correlations among sentiment variables, we estimate their correlations and apply a Cholesky decomposition to this correlation matrix. By multiplying the uncorrelated sentiment matrix with the transposed correlation matrix from Cholesky decomposition, the uncorrelated random sentiment variables are transformed to a correlated sentiment variable matrix.

The control variables are simulated identically for each symbol. The market stock returns, $R_{M,t} \sim G_\gamma(\mu, \sigma)$, are generated from a GEV (Generalized Extreme Value) distribution with the realistic location parameter $\mu = 0.64$, scale parameter $\sigma = 0.35$ and shape parameter $\gamma = 0.20$. These three parameters can be obtained by estimating them from our sample period. Accordingly, $R_{i,t}$, the return of stock symbol i can be generated from simulated $R_{M,t}$ through the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) that states $R_{i,t} - R_{f,t} = \beta_i(R_{M,t} - R_{f,t})$ where β_i represents the systematic risk of stock symbol i that has to be estimated individually, and $R_{f,t}$ is risk-free rate that is fixed as a constant number of 1% annual rate.

Figure 4 demonstrates the association between the negative and positive proportions as distilled via our three projection methods and their simulated future volatility outcomes. Apparently, an asymmetry effect becomes visible. This asymmetry effect is underpinned by confidence bands described below and parallels the well known imbalance of future volatility given good v.s. bad news. The leverage effect depicts a negative relation between the lagged return and the risk resulting from bad news that causes higher volatility. Black (1976) and Christie (1982) find that bad news in the financial market produce such an asymmetric effect on future volatility relative to good news. This leverage effect has also been shown by Bekaert and Wu (2000) and Feunou and Tédongap (2012). In the same vein, Glosten et al. (1993) introduce GARCH with differing effects of negative and positive shocks taking into account the leverage effect.

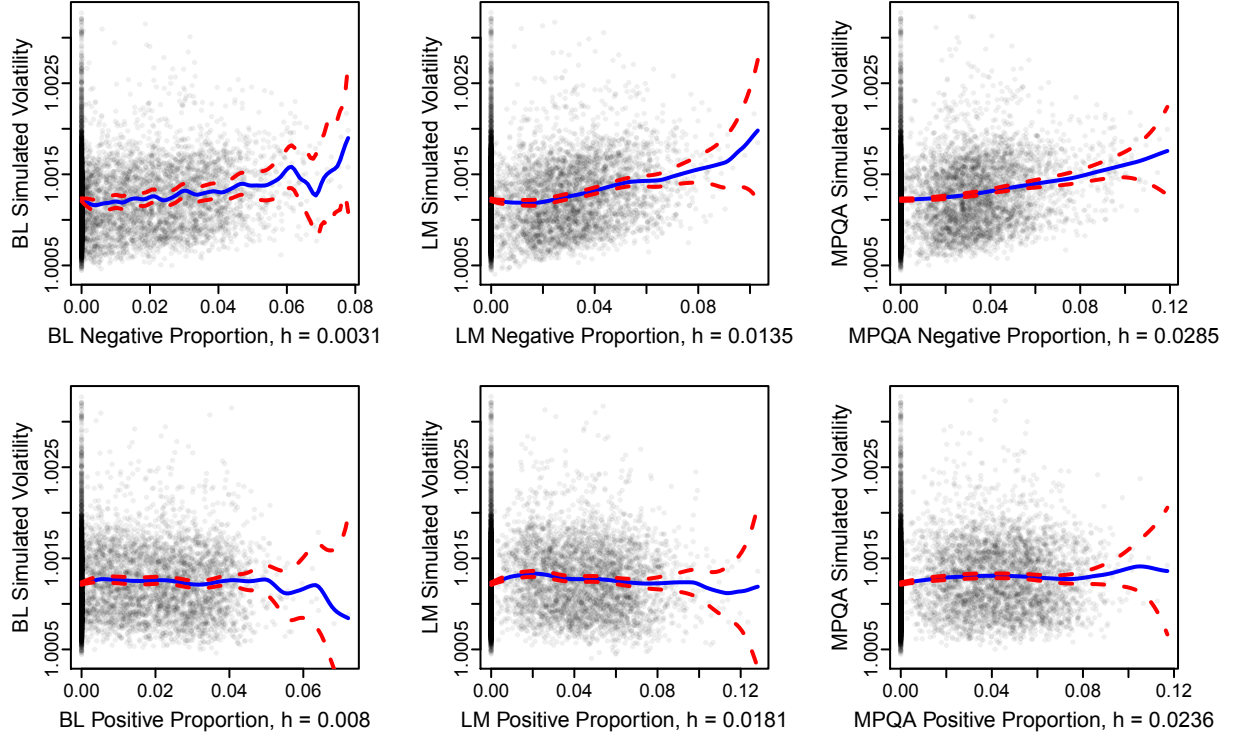


Figure 4: Monte Carlo Simulation based on Entire Sample Results

In Figure 4, we examine this leverage effect by estimating a local linear regression model (solid line) and corresponding 95% uniform confidence bands based on Sun and Loader (1994). Both are estimated using Locfit by Loader (1999) in the R environment.

Loader and Sun (1997) discuss the robustness of this approach and conclude that the results are conservative but reasonable for heavy tailed error distributions. The bandwidth h is automatically chosen by using the plug-in selector according to Ruppert et al. (1995). The clustered points lying on the vertical axis indicate that there is absence of articles after simulating given the assumed frequency for each firms. The range of this cluster from 1.00048 to 1.00328 is caused by the impact from the identical simulated control variables as well as the idiosyncratic impact captured by the residual term.

One observes that slope of the volatility curves given negative sentiment is mainly positive while the curves for positive sentiment seem to be rather flat. We can now compare the confidence bands to address the question whether negative sentiment has a significantly higher effect on the volatility than positive sentiment. This is done by comparing the upper band of the positive proportion with the lower band of negative proportion. For LM the confidence bands of *Pos* and *Neg* do not overlap for sentiment values from 0.042 to 0.094. The same applies to MPQA between 0.051 and 0.91. However, we cannot make a similar statement for the BL sentiment values as the confidence bands are visibly wider for negative sentiment and thus, overlap with the bands of positive sentiment.

3.2 Does Attention Ratio matter?

While people post their text to express their opinions, or the comments to other articles, they are undoubtedly paying attention to the company mentioned by their articles. In this respect the article posting is a revealed attention measure. In fact, in our collected 43,459 articles across the 100 symbol stocks, it is obvious that not every symbol firm shares the same attention. An attention measure might reflect these deviations. Define an attention ratio (symbol wise) as the number of article days divided by its total sample collection days. Here is an example: In our sample period, the symbol “AAPL” (Apple Computer Inc.) attracts the most attention with 0.818 attention ratio. The articles with AAPL involvement arrive in social media almost every day (81.8 days over 100 days). However, the symbol “TRV” (Travelers Companies, Inc.) has the lowest attention ratio, 0.204, which means that one finds a related text source every five trading days, i.e. one week. Different from the “indirect” attention measures from stock indicators such as trading volumes, extreme

returns or price limits, this attention measure is a kind of “direct” measure of investor attention, and shares the same idea as the Search Volume Index (SVI) constructed by Google. Beyond the SVI, our attention can be further projected to “Positive” or “Negative” attention. As mentioned and recalled our main research question two, we are interested in whether the well known asymmetric response (bad vs. good news) is appropriately reflected in the lexical projections. Assumed that investors are more risk-averse, they should be more aware of negative articles and pay more attention to them.

Attention is one of the basic elements in traditional asset pricing models. The conventional asset pricing models assume that information is instantaneously incorporated into asset prices when it arrives. The basis assumption behind this argument is that investors pay “sufficient” attention to the asset. Under this condition, the market price of asset should be very efficient in incorporating any relevant news. In this aspect, the high attention firms should be more responsive to the text sentiment distilled from the articles, and their market prices should reflect this efficiency. As such, the high attention samples stand on the side of the traditional asset pricing models, and the findings from them support the efficient market hypothesis. However, attention in reality is a scarce cognitive resource, and investors have limited attention instead (Kahneman, 1973). Further research on this topic from Merton (1987), Sims (2003) and Peng and Xiong (2006) confirms that the limited attention can affect asset pricing. The low attention firms with very limited attention may ineffectively or insufficiently reflect the text sentiment information, so that their corresponding stock reactions could be greatly bounded. This argument is in accordance with the fact that the limited attention causes stock prices to deviate from the fundamental values (Hong and Stein, 1999), implying a potential arbitrage opportunity.

3.2.1 Descriptive Statistics for the Firms with different Attention Ratios

Grouping the samples by their attention ratios and examining the responses from different attention groups may offer a clue to the aforementioned conjectures. The criterion used to group the sample firms is based on the quantiles of the attention ratio. Firms whose attention ratios are above the 75% quantile value (0.3693) are grouped as “extremely high”, between 50% (0.3026) and 75% quantile value as “high”, between 25% (0.2455) and 50%

quantile as “median”, and lower than 25% quantile as “low”. Table 8 reports across lexical projections the mean value of positive (μ_{Pos}) and (μ_{Neg}) negative sentiment proportions, the average attention ratio, and the number of articles for each attention group. For the constituents in each group, we calculate the average number of article observed over a total of 1255 sample days (5 years). In an extreme case, if the average number of article observed is equivalent to 1255 sample days, it means that on average the articles come everyday. The attention ratio should be equal to one in this case. The “extreme high” receive 55.14% attention ratio, these firms have been looked at almost daily or at least every two days. By contrast, the low attention group at 21.97% receives attentiveness at weekly frequency (5 trading days). By comparing the magnitude of μ_{Neg} , one observes that investors are inclined to express negative sentiments in the “extreme high” group. One may conclude therefore that higher attention is coming with a “negative text”, or inversely speaking: the negative article creates higher attention. This is evident for example in the case of the LM method, the proportion of negative articles on average accounts for 46% in the “extremely high” group. For the constituents in this particular attention group, we find 691 days with articles observed over a total of 1255 sample days (5 years), which is almost three times than the number of articles for the low attention group.

Attention	BL			LM			MPQA			Attention Ratio	Number of Articles
	μ_{Pos}	μ_{Neg}	$Neg > Pos$	μ_{Pos}	μ_{Neg}	$Neg > Pos$	μ_{Pos}	μ_{Neg}	$Neg > Pos$		
Extremely high	0.032	0.016	0.119	0.013	0.014	0.460	0.038	0.013	0.027	0.551	691
High	0.032	0.015	0.113	0.013	0.012	0.403	0.038	0.013	0.031	0.343	430
Median	0.035	0.014	0.083	0.014	0.011	0.339	0.039	0.012	0.027	0.273	356
Low	0.036	0.014	0.086	0.015	0.011	0.333	0.040	0.012	0.031	0.220	264

Table 8: The Summary Statistics for different Attention Ratio Groups

3.2.2 The Results of Attention Analysis

The central interest of this research focuses on the analysis and understanding to which extent distilled news flow and its derived parameters (like attention) impacts the relation between text sentiment and stock reactions. In order to pursue this analysis we employ panel regression designed for the given attention groups, and each panel regression equally comprises 25 sample firms. The results are displayed in Table 9. It shows that for the

“extremely high” the text sentiment carries a major and highly significant influence on future volatility consistently across the three lexical projections. As a caveat though please note that the sentiment effect on volatility shown in Panel A is exclusive for negative news, the stock volatility rarely reacts positive or optimistic news. Panel B summaries the attention analysis on the detrended trading volume. In the case of the LM method, the negative sentiment is strongly and positively correlated with the detrended trading volume for the “median” up to the “extremely high”. As expected, this effect is preeminent for the “extremely high”. The negative sentiment texts effectively drive the trading volume of the firms that have been closely watched by small investors. It is also observable that the significant coefficient of $I_{i,t}$ (arriving article) brings relevant information, and hence creates a growing trading volume. The corresponding analysis for stock returns are less eminent but very reasonable indeed. The stock returns of high attention firms react clearly to the sentiments, they rise for optimistic news and decline for pessimistic consensus. However, the return reaction of lower attention firms is too ambiguous to support this claim.

The collected empirical evidence so far suggests that the distilled news of high attention firms effectively drive their stock volatilities, trading volumes and returns. They are highly responsive to the sentiment across lexical projections. Given the high attention received, any relevant information including the articles made by individual traders has been fully incorporated into their asset prices and dynamics. Due to their efficiency, the article posting and discussing today can predict stock reactions tomorrow. For lower attention firms, one cannot make such a strong claim. Investors may think those firms are negligible and may therefore underreact to the available information. The underreaction from limited attention is likely to cause stock prices to deviate from the fundamental values, an arbitrage opportunity may emerge. Our evidence is in line with Da et al. (2011) in which they support the attention-induced price pressure hypothesis. By using the SVI from Google as attention measure, they find stronger attention-induced price pressure among stocks in which individual investor attention matters most. Beyond their study, we find that the high attention usually accompanies with negative article, and the negative article contributes more to attention and causes more stock reactions, supporting an asymmetric response.

Attention	BL			LM			MPQA		
	$I_{i,t}$	$Pos_{i,t}$	$Neg_{i,t}$	$I_{i,t}$	$Pos_{i,t}$	$Neg_{i,t}$	$I_{i,t}$	$Pos_{i,t}$	$Neg_{i,t}$
Panel A: Future Volatility $\sigma_{i,t+1}$									
Low	0.000 (0.000)	-0.000 (0.002)	0.001 (0.002)	0.000 (0.000)	-0.002 (0.002)	0.002 (0.003)	0.000 (0.000)	-0.001 (0.002)	0.001 (0.003)
Medium	0.000 (0.000)	-0.006 (0.008)	0.008 (0.011)	0.000 (0.000)	-0.005 (0.013)	0.004 (0.013)	0.000 (0.000)	-0.003 (0.008)	0.006 (0.013)
High	-0.000 (0.000)	-0.001 (0.002)	0.004 (0.003)	-0.000 (0.000)	0.002 (0.004)	0.006* (0.003)	-0.000 (0.000)	-0.000 (0.002)	0.006* (0.004)
Extremely High	0.000 (0.000)	-0.001 (0.001)	0.005*** (0.002)	-0.000 (0.000)	-0.002 (0.002)	0.007*** (0.002)	0.000 (0.000)	-0.001 (0.001)	0.004** (0.002)
Panel B: Future Detrended Log Trading Volume $V_{i,t+1}$									
Low	0.072*** (0.017)	-1.185*** (0.370)	0.328 (0.511)	0.048*** (0.013)	-1.077* (0.600)	0.200 (0.549)	0.067*** (0.018)	-0.815** (0.373)	-0.090 (0.634)
Medium	0.071*** (0.016)	-1.139*** (0.351)	1.289*** (0.490)	0.046*** (0.012)	-0.583 (0.568)	1.076* (0.566)	0.083*** (0.017)	-1.126*** (0.359)	0.686 (0.577)
High	0.051*** (0.013)	-0.382 (0.320)	0.622 (0.399)	0.028*** (0.010)	0.894* (0.521)	0.742* (0.447)	0.064*** (0.014)	-0.693** (0.311)	0.573 (0.495)
Extremely High	0.033*** (0.012)	-0.242 (0.278)	0.764** (0.308)	0.025** (0.009)	0.327 (0.455)	0.709** (0.302)	0.049*** (0.013)	-0.623** (0.271)	0.936** (0.373)
Panel C: Future Returns $R_{i,t+1}$									
Low	-0.000 (0.001)	0.010 (0.017)	0.020 (0.024)	-0.000 (0.001)	0.030 (0.028)	0.009 (0.025)	0.000 (0.001)	0.010 (0.017)	-0.011 (0.029)
Medium	-0.001 (0.001)	0.025 (0.017)	0.008 (0.024)	0.000 (0.001)	0.032 (0.027)	-0.037 (0.027)	-0.001* (0.001)	0.039** (0.017)	0.002 (0.028)
High	-0.000 (0.001)	0.025* (0.014)	-0.031* (0.017)	0.000 (0.000)	0.034 (0.022)	-0.050*** (0.019)	-0.000 (0.001)	0.026** (0.013)	-0.042** (0.021)
Extremely High	-0.000 (0.001)	0.014 (0.014)	0.005 (0.015)	-0.001 (0.000)	0.030 (0.022)	-0.025* (0.015)	0.000 (0.001)	-0.007 (0.013)	0.007 (0.018)


*** refers to a p value less than 0.01, ** refers to a p value more than or equal to 0.01 and smaller than 0.05, and * refers to a p value more than or equal to 0.05 and less than 0.1. Values in parentheses are standard errors.

Table 9: Attention Analysis: The Impact on future Volatility, Trading Volume and Returns

3.2.3 Monte Carlo Simulation based on Attention Analysis

Like section 3.1.3, we present a realistic Monte Carlo scenario for different attention groups using the results from Table 9. We keep the parameter settings of the data generation and the calculation of confidence bands as before. Figure 5 summarizes the associations between the negative proportions and the simulated future volatilities across different attention groups. The scatter plots of the extremely high attention panel are quite dense, whereas those of the low attention group are sparser due to its lower frequency of articles. Interestingly, the higher volatilities of extremely high attention firms are prominently driven by negative text sentiment, but have an inverse relationship with positive sentiment.

Nonetheless, through evaluation of the confidence bands we can only conclude for BL and LM that the effect of negative sentiment significantly differs from positive sentiment. The associations in the low attention panel are somewhat ambiguous and therefore no clear causal indication can be given. Indeed, we can support this statement by noting that the confidence regions, given by the bands, of positive and negative sentiment overlap regardless of sentiment value and lexicon. These simulations support the estimations in Table 9 with a strong link found in high attention groups and a preeminent asymmetric response. The firms that have been paid high attentions are more sensitive to the text sentiment than negligible firms. The sentiment effect together with the observable asymmetry are highly influential on stock returns, volatilities and trading volumes. In this sense, their stock reactions are more responsive to the opinions in social media. In other words, they are also more vulnerable to signals from small investors.

The confidence bands in Figures 4 and 5 may be too narrow to reflect the finite sample properties, we therefore consider the bootstrap confidence bands for bounded influence estimators by Härdle et al. (2015) as a more refined approach. The precise algorithm  QRBSGumbel is available on [Quantnet](#).

To illustrate the algorithm consider the sample $\{X_i, Y_i\}_{i=1}^n$ with Y as one of the stock indicators and X may be either the proportion of positive or negative sentiment.

- 1) Compute $\hat{m}_h(x)$ by using the curve estimator proposed by Nadaraya (1964) and Watson (1964):

$$\hat{m}_h(x) = \frac{\sum_{i=1}^n K_h(x - X_i) Y_i}{\sum_{i=1}^n K_h(x - X_i)} \quad (6)$$

where $K_h(u) = \varphi(u/h)/h$ denotes the Gaussian Kernel and set $\hat{\varepsilon}_i \stackrel{\text{def}}{=} Y_i - \hat{m}_h(X_i)$. To ensure robustness against outliers, this estimator is adjusted as proposed in Bickel et al. (1977).

- 2) Compute the estimated conditional distribution function $\hat{F}_{(\varepsilon|X)}(\cdot)$ with Gaussian kernel.
- 3) Construct $j = 1, \dots, J$ bootstrap samples by generating the random variables $\varepsilon_i^* \sim \hat{F}_{(\varepsilon|X=X_i)}$ with $i = 1, \dots, n$ for each sample, and constructing

$$Y_i^* = \hat{m}_g(X_i) + \varepsilon_i^*$$

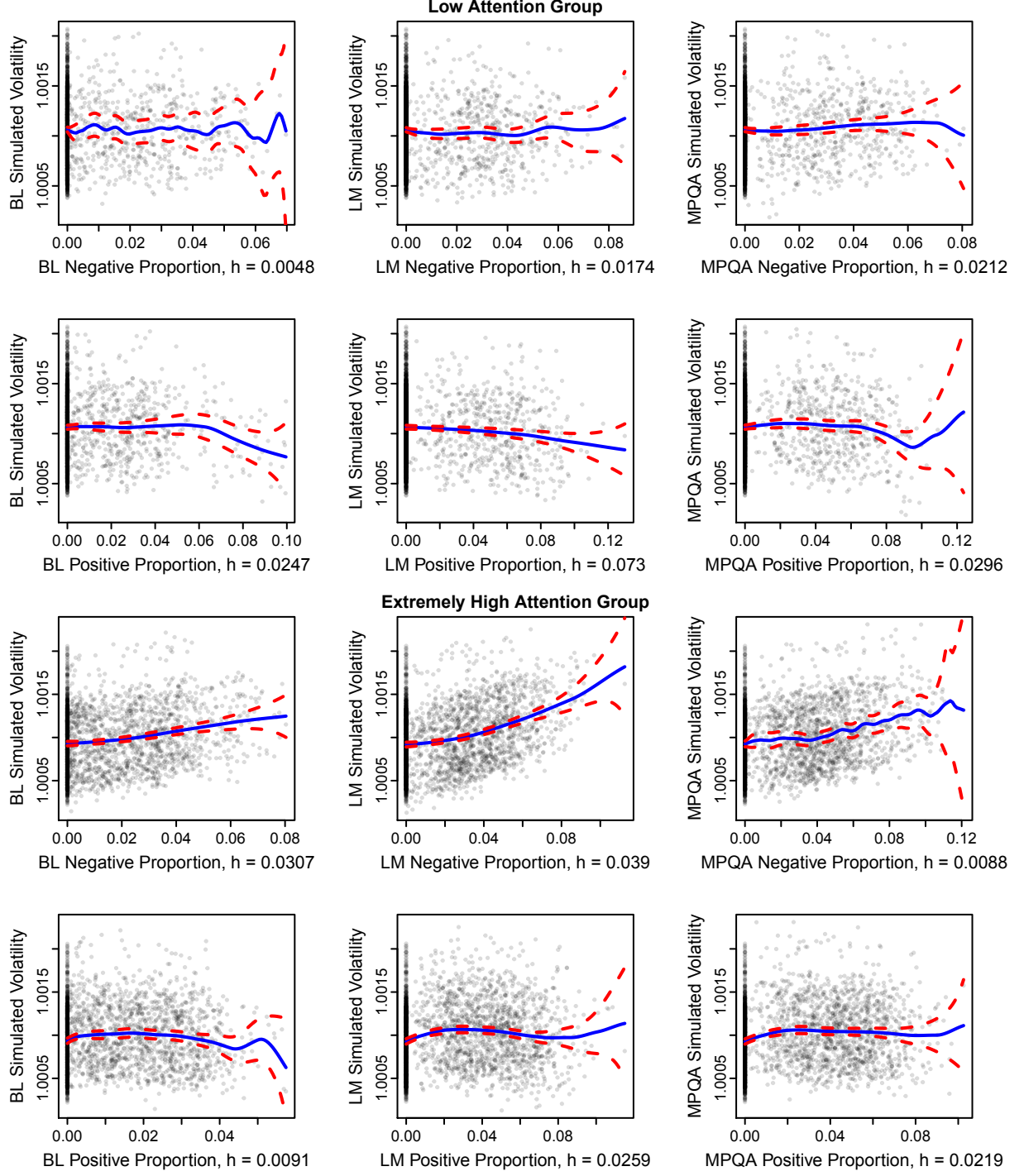


Figure 5: Monte Carlo Simulation based on Entire Sample Results

where $\hat{m}_g(x)$ is calculated similar to (6), but with bandwidth $g \gg h$ chosen such that $\hat{m}_g(x)$ is slightly oversmoothed.

- 4) For each bootstrap sample $\{X_i, Y_i^*\}_{i=1}^n$, smooth the sample with bandwidth h similar to (6), and let $\hat{m}_{h,g}^*(x)$ denote the resulting function. Compute the random variable

$$d_j \stackrel{\text{def}}{=} \sup_{x \in B} [|\hat{m}_{h,g}^*(x) - \hat{m}_g(x)| \sqrt{\hat{f}_X(x) \hat{f}_{(\varepsilon|X)}(x) / \sqrt{\hat{\mathbb{E}}_{\varepsilon|X}\{\psi^2(\varepsilon)\}}}], \quad j = 1, \dots, J$$

based on a finite number of points in the compact support B . Here, $\hat{f}_X(x)$ is the density estimator of the marginal distribution of X , $\hat{f}_{(\varepsilon|X)}(x)$ is the density estimator of the conditional distribution of ε given X , and $\hat{\mathbb{E}}_{\varepsilon|X}\{\psi^2(\varepsilon)\}$ is the estimator of the conditional expectation of $\psi^2(\varepsilon)$ given X , where $\psi(\cdot)$ denotes the ψ -function by Huber (2011) with $\psi(u) = \max\{-c, \min(u, c)\}$ for $c > 0$. Both $\hat{f}_{(\varepsilon|X)}(x)$ and $\hat{\mathbb{E}}_{\varepsilon|X}\{\psi^2(\varepsilon)\}$ are computed using the estimated residuals $\hat{\varepsilon}_i$.

- 5) Calculate the $1 - \alpha$ quantile d_α^* of d_1, \dots, d_J .
- 6) Construct the bootstrap uniform band centered around $\hat{m}_h(x)$

$$\hat{m}_h(x) \pm \left[\sqrt{\hat{f}_X(x) \hat{f}_{(\varepsilon|X)}(x) / \sqrt{\hat{\mathbb{E}}_{\varepsilon|X}\{\psi^2(\varepsilon)\}}} \right]^{-1} d_\alpha^*.$$

Figure 6 shows the results of this approach for LM sentiment values in the extremely high attention group. While the bands are wider as in Figure 5 we can still conclude that the confidence regions of positive and negative sentiment do not overlap for sentiment values between 0.057 and 0.089.

3.3 Sector Analysis

The stock reactions that we analyse in relation to text sentiment can be further segmented into sector specific responses. Given a growing body of literature that has suggested that industry plays a role in stock reactions (see Fama and French (1997), Chen et al. (2007), Hong et al. (2007)), we investigate whether this relation is industry-specific in nature. A detailed analysis of sector specific reactions would go far beyond the scope of this paper and is in fact the subject of research by Bommers et al. (2015). We therefore only highlight a few insights from lexical sentiment for the business sectors. We ignore the ‘‘Telecommunication Services’’ sector since it only contains two stock symbols. Descriptive statistics for the other 8 sectors are displayed in Table 10 across the three lexical projections. It is of interest to

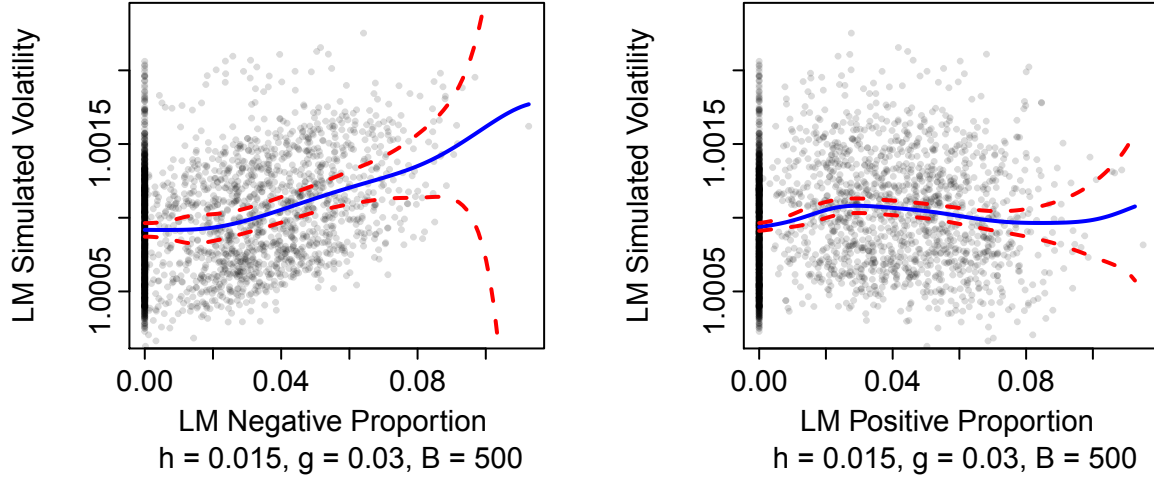


Figure 6: Monte Carlo Simulation of Extremely High Attention Group with Bootstrap Confidence Bands

study the variation of the proportion of negative over positive sentiments across the 8 sectors. One observes that consistently over all lexical projections the financials sector has the highest average discrepancy in negative and positive proportion. By contrast the health care sector has (except for BL) the lowest average discrepancy. Investors show their discrepant opinions or disagreement in a very extreme case of $Neg > Pos = 0.5$, implying that 50% of investors stand on one side and the rest of 50% stand on the opposite side. Table 10 indicates that the financial sector related texts are more divergent in opinions than others and that apparently the health care sector does not receive such adverse opinion positions as the other sectors do. The investors who invest the stocks in health care sector are more likely to reach their shared consensus or convergent agreement.

Sector	BL			LM			MPQA			Attention
	μ_{Pos}	μ_{Neg}	$Neg > Pos$	μ_{Pos}	μ_{Neg}	$Neg > Pos$	μ_{Pos}	μ_{Neg}	$Neg > Pos$	Ratio
Consumer Discretionary	0.034	0.014	0.088	0.014	0.011	0.346	0.038	0.012	0.030	0.332
Consumer Staples	0.034	0.014	0.099	0.014	0.012	0.365	0.037	0.013	0.025	0.324
Energy	0.028	0.015	0.152	0.011	0.011	0.467	0.038	0.014	0.033	0.370
Financials	0.032	0.019	0.195	0.013	0.018	0.594	0.038	0.015	0.045	0.413
Health Care	0.035	0.014	0.059	0.014	0.011	0.344	0.039	0.014	0.031	0.287
Industrials	0.035	0.012	0.069	0.013	0.011	0.355	0.041	0.011	0.018	0.336
Information Technology	0.033	0.015	0.101	0.014	0.012	0.373	0.038	0.023	0.012	0.364
Materials	0.034	0.014	0.097	0.013	0.013	0.498	0.039	0.031	0.013	0.287

Note: this table reports the mean value of positive (μ_{Pos}) and (μ_{Neg}) negative sentiment proportion extracted by the BL, the LM and the MPQA method. The attention ratio is defined as the number of article divided by sample collection for each sector.

Table 10: Summary statistics in each sector

The attention also vary with the sectors. The evidence that financials sector has attracted the highest attention with 0.4128 attention ratio may be attributed to (1) the investors' widespread involvement in this industry because we all need to keep a relationship with banks to deposit our money, trade for securities or some financial reasons; (2) the outbreak of the US subprime crisis and the European sovereign debt crisis have brought the highest attention to this sector; (3) their sensitivity on changes in the economy, monetary policy and regulatory policy. The health care sector, however, is much less attractive and this could be explained by a stable demand and reduced sensitivity to economic cycles. Given these observations we will now continue our thoughts and analysis of stock reactions for these two sectors only, and leave a bundle of interesting issues to further research.

To address the important question of whether there is a sector dependent stock reactions, we further analyze how the text sentiment affects, as reported in Table 11, the future volatility, trading volume and return. In order to do so we employ the panel regression (as described in (4)-(5)) and report the results in Table 11. The variable $I_{i,t}$ was used to indicate the impact of arrival article on this sector and its corresponding stock reactions. The LM and MPQA sentiment projections in financial sectors yielded significant and positive effects from negative proportions, meaning that increasing the negative text sentiments will result in higher volatility. The exclusive response to negative sentiment in financials sector indeed is in line with our entire panel evidence. However, the finding in the health care

sector is obviously reverse since volatility declines with the negative news (measured via BL and MPQA), which is against the leverage effect. Potentially, investor inattention for the health care sector may cause a significant mispricing on the stocks. Investors possibly neglect the news of this sector posted on social media, or this sector has a slow information diffusion that could lead to a delayed reaction.

Sector	BL			LM			MPQA		
	$I_{i,t}$	$Pos_{i,t}$	$Neg_{i,t}$	$I_{i,t}$	$Pos_{i,t}$	$Neg_{i,t}$	$I_{i,t}$	$Pos_{i,t}$	$Neg_{i,t}$
Panel A: Future Volatility $\sigma_{i,t+1}$									
Financials	0.000	-0.003	0.002	0.000	-0.005	0.004*	0.000	-0.003	0.005**
	(0.000)	(0.002)	(0.002)	(0.000)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Health Care	0.000	0.002	-0.004**	0.000	0.001	-0.003	0.000	0.002	-0.004**
	(0.000)	(0.001)	(0.001)	(0.000 0)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)
Panel B: Future Detrended Log Trading Volume $V_{i,t+1}$									
Financials	0.025	-0.159	0.158	0.008	1.526**	-0.237	0.058***	-0.829	-0.130
	(0.018)	(0.444)	(0.457)	(0.014)	(0.728)	(0.421)	(0.021)	(0.535)	(0.610)
Health Care	0.038**	-0.122	-0.176	0.023	0.399	0.242	0.055**	-0.506	0.055
	(0.019)	(0.439)	(0.641)	(0.015)	(0.739)	(0.745)	(0.022)	(0.460)	(0.675)
Panel C: Future Returns $R_{i,t+1}$									
Financials	-0.001	0.036	0.019	-0.001	0.042	0.031	0.001	-0.009	-0.007
	(0.001)	(0.034)	(0.023)	(0.000)	(0.037)	(0.021)	(0.001)	(0.022)	(0.031)
Health Care	0.000	0.004	0.003	0.000	0.013	0.008	-0.000	0.011	-0.021
	(0.000)	(0.016)	(0.024)	(0.000)	(0.027)	(0.027)	(0.000)	(0.017)	(0.024)

*** refers to a p value less than 0.01, ** refers to a p value more than or equal to 0.01 and smaller than 0.05, and * refers to a p value more than or equal to 0.05 and less than 0.1. Values in parentheses are standard errors.

Table 11: Sector analysis: The Impact on future Volatility, Trading Volume and Returns

The trading volume is another stock reaction we may attribute to text sentiments. A striking fact is that the trading volume of both sectors are responsive to text sentiment. The arriving article today will spur trading volume tomorrow. The sentiment distilled from LM method is very effective to financials sector, especially for the optimistic sentiment. The relations under our analysis seem industry-specific and lexicon-specific as well. Unfortunately, the picture is not so clear for stock return reaction. From these analysis, we know that investors indeed pay different attentions to sectors they are of interest, and their attentions effectively govern the equity's variation. Attention constraints in some sectors may affect investors' trading decisions and the speed of price adjustments.

4 Conclusion

In this paper, to analyze the reaction of stocks' future volatility, future detrended trading volume and future returns to social media news, we distill sentiment measures from news using two general-purpose lexica (BL and MPQA) and a lexicon specifically designed for financial applications (LM). We demonstrate that these sentiment measures carry incremental information for future stock reactions. Such information varies across lexical projections, across groups of stocks that attract different level of attention, and across different sectors. The positive and negative sentiments also have asymmetric impact on future stock reaction indicators. A detailed summary of the results is given in table 12 in the Supplementary Material. Compared to the BL and MPQA projections, the negative sentiment derived using the LM projection seems to have some advantages in picking up significant relationship in attention analysis and the positive sentiment derived using the LM projection seems to have some disadvantages in picking up significant relationship in entire sample analysis and attention analysis. But there is no definite picture for which lexicon is the best. This is an important contribution of our paper to the line of research on textual analysis for financial market. Besides, the advanced statistical tools that we have utilized, including panel regression and confidence bands, are novel contributions to this line of research.

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5 Supplementary Material

Table 12 summarizes all the results from entire panel sample analysis, attention analysis and sector analysis. Take the “BL” row in Panel A as an example. Arrival of articles ($I_{i,t}$) and the positive sentiment distilled using the BL method ($Pos_{i,t}$) has no significant impact on future volatility $\sigma_{i,t+1}$ in entire sample analysis, attention analysis or sector analysis; the negative sentiment distilled using the BL method ($Neg_{i,t}$) is significantly positively related to future volatility in entire sample analysis and for the “Extremely High” group in attention analysis, and is significantly negatively related to future volatility for the “Health Care” sector in sector analysis.

Lexicon	Type of Analysis	$I_{i,t}$	$Pos_{i,t}$	$Neg_{i,t}$
Panel A: Future Volatility $\sigma_{i,t+1}$				
BL	Entire Sample	/	/	Positive
	Attention Analysis	/	/	Positive for “Extremely High”
	Sector Analysis	/	/	Negative for “Health Care”
LM	Entire Sample	/	/	Positive
	Attention Analysis	/	/	Positive for “High” and “Extremely High”
	Sector Analysis	/	/	Positive for “Financials”
MPQA	Entire Sample	/	/	/
	Attention Analysis	/	/	Positive for “High” and “Extremely High”
	Sector Analysis	/	/	Positive for “Financials”, Negative for “Health Care”
Panel B: Future Detrended Log Trading Volume $V_{i,t+1}$				
BL	Entire Sample	Positive	Negative	Positive
	Attention Analysis	Positive for all group	Negative for “Low” and “Medium”	Positive for “Medium” and “Extremely High”
	Sector Analysis	Positive for “Health Care”	/	/
LM	Entire Sample	Positive	/	Positive
	Attention Analysis	Positive for all groups	Negative for “Low”, Positive for “High”	Positive for “Medium”, “High” and “Extremely High”
	Sector Analysis	/	Positive for “Financials”	/
MPQA	Entire Sample	Positive	Negative	Positive
	Attention Analysis	Positive for all groups	Negative for all groups	Positive for “Extremely High”
	Sector Analysis	Positive for both sectors	/	/
Panel C: Future Returns $R_{i,t+1}$				
BL	Entire Sample	Negative	Positive	/
	Attention Analysis	/	Positive for “High”	Negative for “High”
	Sector Analysis	/	/	/
LM	Entire Sample	/	Positive	/
	Attention Analysis	/	/	Negative for “High” and “Extremely High”
	Sector Analysis	/	/	/
MPQA	Entire Sample	/	Positive	/
	Attention Analysis	Negative for “Medium”	Positive for “Medium” and “High”	Negative for “High”
	Sector Analysis	/	/	/

The signs of the significant coefficients are given, with a significance level of 0.1.

Table 12: Summary of the Results

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